

# Effects of optimization characteristics and variable antecedent catchment's state on parameter calibration of the Xin'anjiang model

Martins Y. Otache Li Zhijia

(Department of Hydrology and Water Resources, Hohai University, Nanjing 210098, China)

**Abstract:** An attempt was made in this paper to explore how catchment's states along with optimization characteristics affect model behaviour. The Xin'anjiang model was calibrated under daily forecast mode by using various hypothetical initial conditions of the catchment with the SCE-UA optimization algorithm. It was found that initial conditions of the catchment viz-a-viz optimization characteristics have profound effect on the optimized parameters and to a lesser degree on the model process parameter responses; the result showed that variable initial conditions do not have significant influence on the total generated runoff.

**Key words:** SCE; characteristics; optimization; initial conditions; parameter; algorithm

Model calibration is a major aspect of hydrologic modelling with the underlying goal for generating and organizing quantitative estimation of information for water resources planning, design, and operation. More concisely, the main essence is to estimate rates of water movement overland, underground, or within streams; amounts of water stored in the soil, or in natural water bodies and its transient nature. For the past several decades, using the primary approach of transforming rainfall (model input) to streamflow (model output) through a number of interconnected mathematical functions (each representing a certain component of the hydrological cycle), a wide range of conceptual rainfall-runoff models has been developed.

In the views of Gan, et al.<sup>[1]</sup>, one thing is paramount, and that is, the selection of a model should address three major issues; one of interest here, within the context of this discourse, is that “the conceptual base of the model should capture the major hydrological processes of the catchment”. This view is considered highly relevant against the fact that a hydrological model represents runoff processes in a manner that can be used to estimate ① How the prototype physical system would respond to sequences of external stimuli (usually precipitation); ② The frequency distribution of responses of interest (high or low flows); or ③ How changes to the system would alter the response. The representation may be a physical model providing

scaled-down duplication of the prototype system, an analog model, which uses another physical system that is more economically constructed but has similar response characteristics, or a mathematical model that is programmed for a digital computer<sup>[2]</sup>.

Though this might be the case, conceptually realistic models can produce erroneous results if they are not properly calibrated. Model calibration is either done manually or by a combination of manual effort and automatic procedures<sup>[3]</sup>. This may be done by assignment of initial values to parameters which are then optimized entirely by an automatic procedure or by calibrations done manually. Whether or not a model is calibrated by either of the two procedures, there is no certainty of obtaining a unique set of optimal parameters for a conceptual rainfall-runoff model<sup>[4, 5]</sup>. Reasons adduced for this include calibration data with limited information, data with measurement errors, spatial variability of rainfall or catchment properties poorly represented by point measurements, and also the fact that CRR models suffer from model structure and parameter identifiability problems.

Traditionally, “when an automatic calibration procedure is used, the final model parameters derived depend primarily on four elements: ① Optimization algorithm; ② Objective functions; ③ Calibration data; and ④ Model structure and identifiability of model parameters”<sup>[1]</sup>. For obvious reasons, each element exerts a seeming degree of influence on the outcome of model calibrations. In view of this, the focus of this paper is on the effects of a catchment's

Received 2003-06-27.

**Biographies:** Martins Y. Otache (1968—), male, graduate, Nigeria, martinso3@yahoo.com; Li Zhijia (corresponding author), male, doctor, professor, lizhijia@public1.ptt.js.cn.

state and the characteristics of the optimization algorithm on the model calibration with respect to its optimized values.

## 1 Objective

To calibrate a hydrologic model, the hydrologist must specify values for its "parameters" in such a way that the model's behaviour closely matches that of the real system it represents. In some cases, the appropriate values for a model parameter can be determined through direct measurements conducted on the real system. However, in a great many situations, the model parameters are conceptual representations of abstract watershed characteristics and must be determined through a trial-and-error process which adjusts the parameter values so that the model response matches the historical input-output data<sup>[6]</sup>.

With this as the background, the cardinal objectives of this discourse are to examine the effects of varying initial conditions of the catchment and characteristics of the optimization algorithm on parameter optimized values within the following underlying areas of interest, to wit:

- Effect of change in initial state of catchment on the behaviour of the model;
- Parameter responses under varying iteration runs;
- Effect of change or variations in random seed value (RSV), an SCE-UA parameter on the model behaviour.

The aim here is to ascertain the existence or non-existence of significant change in catchment process behaviour viz-a-viz the overall corresponding parameter response.

## 2 Test Catchment/Hydrologic Data

For this study, the Misai catchment was used. The Misai catchment (in Zhejiang province, China) is located south of the 29°30' latitude and of the 118° 30' longitude. It has a total of six precipitation measuring stations identified according as Qixi, Majin, Yanxi, Daxibian, Huanglinkang, and Misai, respectively (see Fig.1 and Tab.1). The total area of the catchment stands at 797 km<sup>2</sup>. The area is mountainous with thick vegetation cover, very fertile with a highly permeable upper layer soil profile. In addition, the ground water is high and accounts for about 40% of yearly runoff. Also worthy of note is that the catchment is located in

an area which is humid with a notable, fairly high precipitation; yearly average rainfall is about 1 500 to 2 000 mm.

**Tab.1** Sub-catchment areas of the Misai basin

Number	Name of the sub-catchment	Area/km <sup>2</sup>
1	Qixi	207.22
2	Majin	162.59
3	Yanxi	130.71
4	Daxibian	131.51
5	Huanglinkang	89.26
6	Misai	75.71



**Fig.1** Misai catchment

To calibrate the Xin'anjiang model for the purpose of this study, hydrologic data for a period of five water years, i.e., 1982 to 1986 was used. This includes precipitation, evaporation, and discharge; all these constitute the input data for the model under study.

## 3 Conceptual Model

Over the years, the study of conceptual rainfall-runoff models has been at the centre stage in the field of hydrology. In the world of hydrology, the entire principle is based on imperfect observations in a complex and sometimes discontinuous domain<sup>[7]</sup>. The attendant effect of this is the seeming tremendous range of information that is required and concomitantly thus calls for analysis in order to thoroughly appreciate the inherent characteristics. To address this difficult but important issue, the whole idea of hydrologic modelling evolved over time.

In recognition of this end, the Xin'anjiang model was developed in 1973 by the East China College of Hydraulic Engineering (now Hohai University), with the underlying aim to forecast flows to the Xin'anjiang reservoir<sup>[8]</sup>. The Xin'anjiang model has a hierarchical structure with two distinct conceptual storages (see Fig.2), tension water and free water; to account for soil moisture process regime in conjugal relationship with precipitation, the consequent runoff generation and separation constituents.

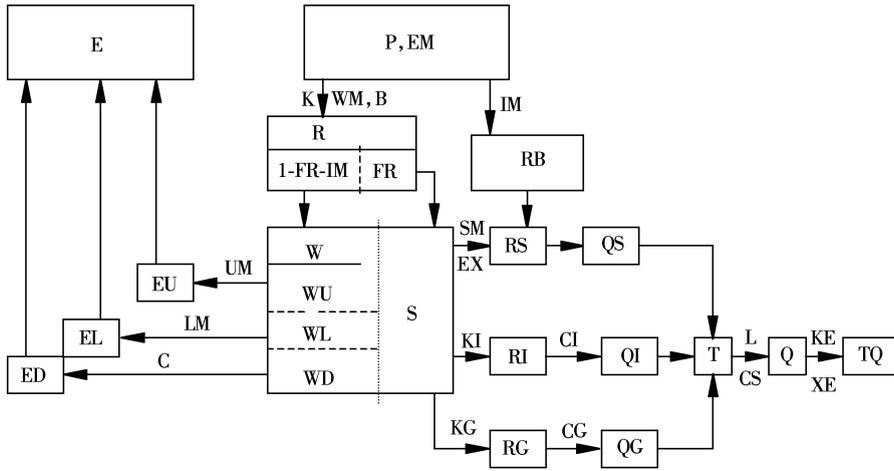


Fig. 2 Flow chart for the Xin'anjiang model<sup>[9]</sup>

## 4 Optimization Algorithm

The shuffle complex evolution method (SCE-UA) of Duan et al.<sup>[10]</sup> was used for this study. The basic reason for this derives from the fact that the SCE method has been widely applied for calibration of various conceptual rainfall-runoff models, including the Sacramento model<sup>[5,6,11,12]</sup>, the Tank model<sup>[13,14]</sup>, and the Xin'anjiang model<sup>[1,5]</sup>.

More importantly, it was adopted in view of its versatility. It is a global optimization method which is classified as probabilistic because of its capability in evaluating the objective function at randomly spaced points in the feasible parameter space. To add, its versatility is epitomized by its representative nature; it represents a synthesis of the best features of several methods. Concisely, the SCE method combines different search strategies including: ① Competitive evolution; ② Controlled random search; ③ The simplex method; and ④ Complex shuffling.

## 5 Study Protocol

The study approach is patterned after Ranjit<sup>[15]</sup> who did a similar work on four Nepalese catchments namely, Bagmati basin, Gandaki 1 and 2, and the Tamor basin. By using the SCE algorithm, attempt was made to address the stated objectives listed in section 2.

The SCE-UA method includes various algorithmic parameters; the most important being the number of complexes whose choice is left at the discretion of the user and more on the complexity of the problem at hand. Here, the number of complexes was set to a default value of 32. In view of the fact that the objective function plays a crucial role in model calibration, a balanced aggregate objective function was used (see appendix). More concisely, in

realization of the stated objectives, three sets of abstract initial catchment's conditions were chosen purportedly to represent the catchment's state at various times and the model was then calibrated using the 15 parameters with the aim of examining their responses for each initial condition. In addition to the above, various iteration runs along with varying random seed value: RSV (constant random number generation) were used as characteristics of the optimization algorithm and the corresponding behaviour of the model parameters was similarly looked at. The performance measures used in the analysis were the Nash-Sutcliffe efficiency ( $D_y$ ), overall volume error ( $V_{ERR}/\%$ ), and objective function value along with noticeable change in parameter optimized values for each of the stated objectives.

## 6 Discussion

As stated in the preceding sections, statistical indices selected to evaluate the performance of the model with respect to the stated objectives of this discourse are the Nash-Sutcliffe coefficient of efficiency ( $D_y$ ), objective function value, percentage volume error, and more importantly, the behaviour of the parameters; in this case, existence or non-existence of change (stability or otherwise) in optimized values.

### 6.1 Optimizing with varying iteration run

To appreciate the effect of the characteristics of the optimization algorithm on the response of the model in terms of its optimized parameter values, several iteration runs were tried. Iteration runs of 3 000, 4 000, 5 000, 6 000, 7 000, 8 000, 9 000, 10 000, 15 000, and 20 000 were tried and results and statistics compared. The initial condition of the catchment as well as SCE parameters in this case except number of

iterations are indicated below in Tab.2 and the accompanying note.

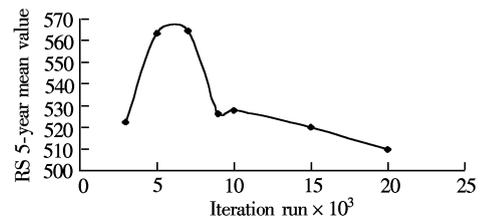
**Tab.2** The hypothetical initial condition of catchment

W	WU	WL	FR	S	QS	QI	QG
125	25	60	0.1	0.3	1.0	0.2	85

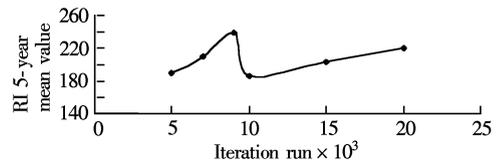
Note: Number of complex is 32; random seed value (RSV) is - 87.

For iteration runs of 3 000 and 4 000, there was no change both in parameter values and process parameter statistics. The situation is the same between iteration run of 5 000 and 6 000. The implication of this is that there is some degree of stability in the parameter at lower iteration runs. But from 7 000 to 9 000, staggering fluctuation in both parameter optimized values, objective function values and process parameter statistics was observed; this trend was pronounced at relatively higher iteration runs (see Tab.3).

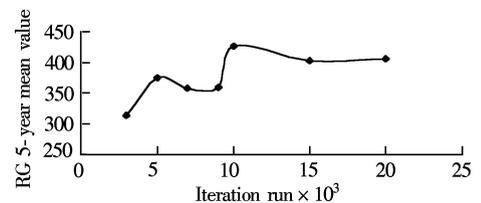
It was discovered that the situation in the case of process parameter response was distinctly different. Interflow runoff (RI) is generated more at lower iteration runs relatively to other runoff components; for instance, the 5-year mean RI stands at 320.3 for iteration run of 3 000 (see Tab.4) whereas at 7 000 and 10 000, surface runoff (RS) and ground water runoff (RG) respectively attained their peak values. Conversely, in general, there is an undulating trend in the responses of these process parameters (see Fig.3, Fig.4, and Fig.5). To be precise, RS decreases with increase in iteration run whereas RG, at higher runs is linear and



**Fig.3** Surface runoff (RS) vs. iteration run



**Fig.4** Interflow RI vs. iteration run



**Fig.5** Ground water runoff RG vs. iteration run

marginally constant; but for RI, it is a swinging wave-like behaviour. This trend practically connotes instability in parameter responses under this scenario. Similarly, further analysis was carried out using different random seed values (RSV) under the same initial condition as iteration run (see Tab.5 for parameter values).

**Tab.3** Results of the calibration

Iteration run	Function value	Parameters														
		K	IM	B	WUM	WLM	WDM	C	SM	EX	CG	CI	CS	KG	KI	XE
10 000	190.555	1.006	0.014	0.351	16.712	81.219	37.522	0.146	17.392	0.622	0.906	0.512	0.010	0.399	0.174	0.371
15 000	189.778	1.057	0.010	0.353	13.389	85.670	43.689	0.096	16.714	0.540	0.903	0.552	0.010	0.383	0.194	0.381
20 000	184.447	1.040	0.010	0.379	13.495	81.874	41.418	0.162	16.364	0.509	0.901	0.551	0.011	0.394	0.215	0.383
Variation/%	3.21	4.82	NA	7.43	19.88	5.19	14.12	40.74	5.91	18.17	0.55	7.25	9.09	4.01	19.07	3.13

Note: Variation > 10% means considered a significant change; NA means not applicable.

**Tab.4** Runoff component's overall response to varying iteration runs

Process parameters (5-year mean value)	Iteration						
	3 000	5 000	7 000	9 000	10 000	15 000	20 000
RS	522.5	563.4	564.5	526.2	527.9	520.1	510.0
RI	320.3	189.5	210.5	239.0	185.7	203.4	220.6
RG	312.9	375.0	358.3	359.3	426.8	401.7	405.4

**Tab.5** Parameters vs. RSV

Iteration run	Function value	Parameters														
		K	IM	B	WUM	WLM	WDM	C	SM	EX	CG	CI	CS	KG	KI	XE
- 67	189.42	1.042	0.010	0.388	12.957	85.153	42.746	0.165	16.279	0.502	0.901	0.561	0.010	0.388	0.221	0.383
- 77	189.44	1.022	0.010	0.381	15.350	85.089	42.227	0.149	16.408	0.508	0.900	0.558	0.101	0.395	0.209	0.383
- 87	184.45	1.040	0.010	0.379	13.495	81.873	41.418	0.162	16.364	0.509	0.901	0.551	0.011	0.394	0.214	0.383

## 6.2 Variable initial catchment's state

In the SCE-UA method, initial condition or state

of the catchment is considered as a parameter along with the initial and parameter range which are to be supplied before the commencement of the calibration.

For this case, W: tension water storage; WU: upper layer tension water storage; WL: lower layer tension water storage; FR: runoff contributing area factor; S: free water storage; QS: surface flow; QI: interflow; QG: ground water flow respectively constitute the state parameters.

As illustrated in Tab.6, I, II, and III respectively represent the initial state of the catchment at various times while calibration details are given in Tab.7.

**Tab.6** Initial state of the catchment

Parameters	State/mm		
	I	II	III
W	125	65	125
WU	30	10	30
WL	90	30	90
FR	0.1	0.2	0.1
S	1.5	0.1	1.5
QS	1.5	1	1.5
QI	0.5	2	0.5
QG	10	2	1.0

Note: Details of SCE parameters: number of iteration is 10000; RSV is - 87; number of complexes is 32.

**Tab.7** Optimized parameter values and statistics for each state

Parameters	State/mm			Variation range	Variation/%
	I	II	III		
K	1.073	1.074	1.011	0.063	5.87
IM	0.012	0.011	0.017	NA	NA
B	0.385	0.369	0.325	0.060	15.58
WUM	14.966	12.529	17.185	4.660	27.09
WLM	78.844	69.001	63.046	15.800	20.04
WDM	21.908	22.735	25.034	3.130	12.49
C	0.112	0.136	0.137	0.025	18.25
SM	17.435	15.791	16.473	1.640	9.43
EX	0.710	0.510	0.602	0.200	28.17
CG	0.956	0.950	0.946	0.010	1.05
CI	0.652	0.632	0.649	0.020	3.07
CS	0.105	0.013	0.010	0.095	90.48
KG	0.270	0.336	0.319	0.066	19.64
KI	0.339	0.330	0.304	0.035	10.32
XE	0.384	0.392	0.393	0.009	2.29
Function value	180.52	180.74	180.54	0.22	0.12

Note: variation > 10%: considered significant; variation: max - min.

The optimized values for some of the parameters show insignificant variation for the different initial conditions whereas others exhibit considerable responses as a result of the induced change. By varying the initial conditions, parameters like WUM, WLM, C, SM, EX, CI, CS, KG, KI, and B are sensitive, showing discernible change in their optimized values. Similarly, the responses of XE, CI, and K respectively are insignificant considering the fact that percentage variation greater than ten is adjudged to be sensitive under this condition. Concisely, in the case of parameter XE, the response is at variance with the

findings of Ranjit<sup>[15]</sup>. On the other hand, the behaviour of IM (impervious area parameter) was not taken into due consideration in the optimization, for it is a physical variable and ought to be determined by physical measurement on the field for a realistic appreciation of its value.

The objective function value shows some marginal difference for all the three initial catchment's state. Function value for state I is relatively the lowest in all thus indicating that the model responded positively well for this initial condition. Sequel to this, the calibrated parameter values under this condition are taken to be the best relatively. The physical implication of this scenario is simple: that is, there is an equally corresponding significant response of the parameters SM, EX, CG, CI, CS, and KI as depicted by their optimized values culminating in a high mean surface runoff (see Tab.8). However, this does not reflect in any great change in the values of the total generated runoff for the differing state of the catchment. The overall percentage change of values between the different states is highly marginal; precisely, the percentage variation in total generated runoff stands at 2.40%.

**Tab.8** Statistics of the calibration analysis

Process parameters (5-year mean value)	State/mm		
	I	II	III
R	1 114.61	1 124.52	1 142.05
RS	504.84	489.25	521.83
RI	339.65	314.67	302.55
RG	270.15	320.60	317.70
$Q_{OBS}$	1 149.01	1 149.01	1 149.01
$Q_{CAL}$	1 119.35	1 125.25	1 142.30
$V_{ERR}/\%$	3.04	3.52	0.96
$D_y$	0.933	0.932	0.931

On the other hand, though state I has the lowest objective function value, this effect does not translate significantly well into a better percentage volume error (see Tab.8) in the process parameter statistics. Here, there is a glaring twist though the 5-year mean cumulated Nash-Sutcliffe efficiency is almost the same.

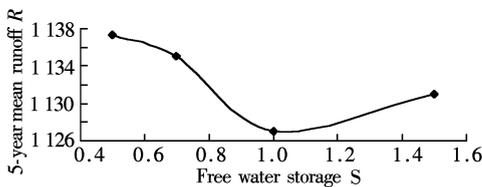
To demonstrate the effect of variable initial condition or state of the catchment on the model response, an attempt was made to critically look at the specific effect of varying free water storage S on the overall model responses. As illustrated in Tab.8 and Fig.6, the 5-year mean runoff produced under differing free water storages S does not in any way differ so much but like in the preceding cases, only parameter C showed meaningful variation and to a lesser degree, KI. For better understanding of these issues

mentioned, refer to Tab.9. What is of more interest here is the model overall response in the light of these varying changes in free water storage condition. From

**Tab.9** Summary of the analysis for variable free water storage S

S	$R_{av}$	K	IM	B	WUM	WLM	WDM	C	SM	EX	CG	CI	CS	KG	KI	XE
0.3	1136.03	1.040	0.010	0.379	13.495	81.874	41.418	0.162	16.364	0.509	0.901	0.551	0.011	0.394	0.215	0.383
0.5	1137.30	1.030	0.010	0.389	14.270	84.187	43.126	0.170	16.759	0.504	0.900	0.539	0.010	0.396	0.198	0.380
0.7	1135.04	1.034	0.010	0.390	14.734	83.100	41.323	0.160	16.923	0.503	0.900	0.532	0.010	0.394	0.198	0.387
1.0	1127.06	1.032	0.010	0.386	14.091	83.621	42.226	0.166	16.843	0.506	0.901	0.528	0.010	0.393	0.204	0.384
1.5	1131.03	1.047	0.010	0.390	13.885	84.524	41.567	0.135	17.067	0.500	0.901	0.546	0.010	0.380	0.194	0.382
Variation/%	0.90	1.62	NA	2.82	8.41	1.68	4.18	20.59	4.12	1.77	0.11	4.17	9.09	4.04	9.77	1.81

Note: SCE parameter details; RSV is - 87; iteration run is 20000;  $R_{av}$  is 5-year mean runoff; initial condition is the same as in optimization under varying iteration number.



**Fig.6** Mean cumulated 5-year runoff vs. free water storage S

## 7 Conclusions

The shuffle complex evolution (SCE-UA) optimization algorithm was used for the calibration of the Xin'anjiang model in a daily forecast mode. Based on the findings of this study, it is succinctly clear to an extent that initial state of the catchment and optimization characteristics do impact greatly on the parameter responses of a model during calibration process. It is important to state that though this might be the case, by and large, initial conditions of the catchment do not really influence the total generated runoff much as could be seen in Tab.8. For short time duration, the effect could be appreciable but the long time effect is seemingly negligible. More generally, the objective function should be an indicator of the measure of the runoff generated but in this case, a balanced aggregate function was used; placing emphasis on the whole runoff process rather than runoff volume alone.

In specific terms, the model exhibits a variant behaviour under variable antecedent catchment's conditions; this greatly affirms the need for a proper assessment of the catchment's hydrological regime prior to any model calibration exercise and its subsequent application. From the results, it could be inferred that parameters B, C, KG, KI, WUM, WLM and CS are largely affected by the initial conditions of the catchment, this conforms to Ranjit<sup>[15]</sup>; though, in respect to initial condition, free water storage S exhibits a non-linear, more or less sinusoidal behaviour in relation to the generated runoff.

On the other hand, parameters like EX, KI, C and WUM show some sensitive responses under varying

Fig.6, it could be inferred that the relationship existing between the same and the runoff produced is non-linear, precisely sinusoidal.

optimization characteristics; for instance, varying iteration runs. Similarly too, the results also do indicate marginal differences in both function values and optimized parameter values when calibration was done with different random constant number generation (RSV). In the global optimization scheme, the search is usually tied to the numbers of iteration and complexes as these limit the search space. Thus to a large extent, the results indicate that the parameter values obtained under these iteration runs are conceptually realistic but not adequate in view of global optimum point.

In totality, the parameters EX, KI, and C seemed to show appreciable variations under the conditions considered herein. Thus to enhance the chances for better results, it is imperative to ascertain correct initial conditions of the catchment though this might be a difficult task. This can better be done through more practical realistic means other than the usual practices of relying heavily on the modeler's weight of experience in the art.

**Acknowledgement:** FFS: a flood forecasting system (using SCE algorithm) prepared by H. A. P. Hapurachchi and Li Zhijia, 2001 was used for analysis.

### Appendix Objective functions

Overall volume error:

$$F_1(\theta) = \left| \frac{\sum_{i=1}^n W_i [Q_{obs,i} - Q_{sim,i}(\theta)]}{\sum_{i=1}^n W_i} \right|$$

Overall root mean square error (RMSE):

$$F_2(\theta) = \left\{ \frac{\sum_{i=1}^n w_i^2 [Q_{obs,i} - Q_{sim,i}(\theta)]^2}{\sum_{i=1}^n w_i^2} \right\}^{\frac{1}{2}}$$

Average RMSE of peak flow events:

$$F_3(\theta) = \frac{1}{M_p} \sum_{j=1}^{M_p} \left[ \frac{\sum_{i=1}^{m_j} w_i^2 (Q_{\text{obs},i} - Q_{\text{sim},i})^2}{\sum_{i=1}^{m_j} w_i^2} \right]^{\frac{1}{2}}$$

Average RMSE of low events:

$$F_4(\theta) = \frac{1}{M_L} \sum_{j=1}^{M_L} \left\{ \frac{\sum_{i=1}^{m_j} w_i^2 [Q_{\text{obs},i} - Q_{\text{sim},i}(\theta)]^2}{\sum_{i=1}^{m_j} w_i^2} \right\}^{\frac{1}{2}}$$

Aggregate objective function:

$$F_{\text{agg}}(\theta) = \left\{ [g_1 f_1(\theta)]^2 + [g_2 f_2(\theta)]^2 + [g_3 f_3(\theta)]^2 + [g_4 f_4(\theta)]^2 \right\}^{\frac{1}{2}}$$

## References

- [1] Gan T Y, Dlamini M E, Biftu G F. Effects of model complexity and structure, data quality, and objective functions on hydrologic modelling [J]. *J Hydrol*, 1997, **192**: 81 - 103.
- [2] James L Douglas. Selection, calibration and testing of hydrological models [A]. In: Haan C T, Johnson H P, Brakenslek D L, eds. *Hydrological Modelling of Small Watersheds*, ASAE [C]. 1982(5):437 - 449.
- [3] Gan T Y. Application of scientific modelling of hydrological response from hypothetical small catchments to assess a complex conceptual rainfall-runoff model [R]. Water Resources Series Technical Report, No.111. Seattle: Department of Civil Engineering, University Washington, 1988.
- [4] Gupta V K, Sorooshian S. The automatic calibration of conceptual models using deterministic based optimization algorithms [J]. *Water Resources Research*, 1985, **21**(4): 473 - 485.
- [5] Gan T Y, Biftu G F. Automatic calibration of conceptual rainfall-runoff models: optimization algorithms, catchment conditions and model structure [J]. *Water Resources Research*, 1996, **32**(12): 3513 - 3524.
- [6] Yapo P O, Gupta, H V, Sorooshian S. Multi-objective global optimization for hydrological models [J]. *J Hydrol*, 1998, **204**: 83 - 97.
- [7] Richard H M, William S. *Hydrological modelling: statistical methods and applications* [M]. Prentice-Hall Publishing, 1986. 1 - 10.
- [8] Zhao R J, Zhuang Y L, Fang L R, et al. The Xin'anjiang model in hydrological forecasting [A]. *Proceedings of the Oxford Symposium* [C]. IAHS Publication, 1980, **129**:351 - 356.
- [9] Zhao R J. The Xin'anjiang model [J]. *J Hydrol*, 1992, **135**:371 - 381.
- [10] Duan Q, Sorooshian S, Gupta V K. Effective and efficient global optimization for conceptual rainfall-runoff models [J]. *Water Resources Research*, 1992, **28**(4): 1015 - 1031.
- [11] Sorooshian S, Duan Q, Gupta V K. Calibration of rainfall-runoff models: application of global optimization to the Sacramento soil moisture accounting model [J]. *Water Resources Research*, 1993, **29** (4): 1185 - 1194.
- [12] Duan Q, Sorooshian S, Gupta V K. Optimal use of the SCE-UA global optimization method for calibrating watershed models [J]. *J Hydrol*, 1994, **158**: 265 - 284.
- [13] Tanakamaru H, Burges S J. Application of global optimization to parameter estimation of the Tank model [A]. In: *Proceedings of the International Conference on Water Resources and Environmental Research* [C]. Kyoto, Japan, 1996, **2**: 39 - 46.
- [14] Cooper V A, Nguyen, V T V, Nicell J A. Evaluation of global optimization methods for conceptual rainfall-runoff model calibration [J]. *Water Sci Technol*, 1997, **36**(5): 53 - 60.
- [15] Ranjit M. Application of Xin'anjiang model in the Nepalese terrain and optimization of parameters [D]. Nanjing: Department of Hydrology and Water Resources, Hohai University, 2001. 7; 55 - 67.

# 最优化特性和变化的流域初始状态 对新安江模型参数的影响

Martins Y. Otache 李致家

(河海大学水资源环境学院, 南京 210098)

**摘要** 本文对流域状态和最优化特性是如何影响模型功能方面进行了研究. 在假设流域诸多初始条件下, 使用 SCE-UA 优化算法通过日模型率定新安江模型. 结果发现流域的初始条件和最优化特性对待优化的参数有非常大的影响, 并且使模型过程参数的响应程度变小. 研究结果表明变化的初始条件对总产流的影响并不是太大.

**关键词** SCE; 特征; 最优化; 初始条件; 参数; 算法

**中图分类号** P338.9